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Crop Detection and Maturity Classification Using a YOLOv5-Based Image Analysis

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Abstract

In recent years, the accurate identification of chili maturity stages has become essential for optimizing cultivation processes. Conventional methodologies, primarily reliant on manual assessments or rudimentary detection systems, often fall short of reflecting the plant's natural environment, leading to inefficiencies and prolonged harvest periods. Such methods may be imprecise and time-consuming. With the rise of computer vision and pattern recognition technologies, new opportunities in image recognition have emerged, offering solutions to these challenges. This research proposes an affordable solution for object detection and classification, specifically through version 5 of the You Only Look Once (YOLOv5) model, to determine the location and maturity state of rocoto chili peppers cultivated in Ecuador. To enhance the model's efficacy, we introduce a novel dataset comprising images of chili peppers in their authentic states, spanning both immature and mature stages, all while preserving their natural settings and potential environmental impediments. This methodology ensures that the dataset closely replicates real-world conditions encountered by a detection system. Upon testing the model with this dataset, it achieved an accuracy of 99.99% for the classification task and an 84% accuracy rate for the detection of the crops. These promising outcomes highlight the model's potential, indicating a game-changing technique for chili small-scale farmers, especially in Ecuador, with prospects for broader applications in agriculture.

Keywords:
Chili Peppers;
Dataset;
Detection;
Classification;
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1- Introduction

Agriculture has played a pivotal role in fostering the growth and development of societies by supplying the necessary food to maintain and expand populations [1]. Nonetheless, as the human population expands, this activity confronts a series of new issues and hurdles [2]. The growing demand for increased production places significant strain on farmers to achieve higher yield quotas, with numerous factors that may undermine this objective [3]. From a broader macro-level perspective, technologies such as remote sensing and intelligent computing are employed to estimate the planted area of a region and classify different crops. Moreover, these technologies facilitate detecting and mapping agricultural field boundaries [4]. On a micro level, crop inspection, detection, and classification are integral parts of the farming process [5]. Classifying the maturity state of crops enables farmers to assess the freshness of the crops they are packing and distribute their products without risking spoilage or reduced prices [6]. Detecting a crop's presence while verifying its maturity state is typically lengthy and repetitive but could be expedited by utilizing emerging technologies like Machine

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Learning (ML) and Deep Learning (DL). These models also have the potential to identify crop abnormalities, including diseases and pests [7, 8]. However, the efficient detection of fruit and vegetable species and their respective states from images presents several challenges to be addressed [9].

Artificial Intelligence (AI) models have emerged as indispensable tools for farmers, facilitating the detection and classification of crops and providing solutions to many challenges [6]. When properly calibrated, AI models equipped with computer vision have the potential to minimize identification errors and boost productivity during harvest [10]. These models can be integrated into robotic machinery, which can operate autonomously or under remote control [11]. Such technology proves particularly advantageous in vast farms with a diverse array of plant species, as it can accurately pinpoint crops and distinguish between fruits and leaves, a task particularly daunting in crops like chili peppers due to their similar morphology [12].

When it comes to fruit crops, a diverse array of classification techniques has been employed [8]. Machine Learning, Deep Learning, and Computer Vision applied to pattern recognition have gained widespread acceptance due to their commendable performance in image recognition [13]. Particularly noteworthy are the recent advancements in deep learning and Convolutional Neural Networks (CNN), which have spearheaded the development of rapid models capable of versatile detections and classifications [8]. A compelling illustration of their efficacy can be found in Badeka et al. [14], where various CNN models underwent rigorous testing for grape detection. You Only Look Once (YOLO) is of particular significance, which warrants special attention [15]. Renowned for its superior performance and adaptability, it has been applied across diverse crops, including apples [16, 17], strawberries [18], and chili peppers [19], highlighting the transformative potential of AI in reshaping agricultural practices.

In contrast to traditional machine learning algorithms, deep learning excels in extracting insights from unstructured or unlabeled data. This remarkable capability simplifies crucial tasks such as crop health monitoring [20], disease identification [21], weed detection [22], and yield estimation [23], traditionally recognized for requiring extensive human expertise and labor. An illustrative example is the capacity of deep learning models to analyze drone or satellite images of farmland, facilitating the early detection of plant diseases or infestations [24]. This convergence of advanced technologies and agricultural practices holds promise for revolutionizing the landscape of crop management.

Our research focuses on the agricultural landscape of Ecuador, with a particular emphasis on chili pepper cultivation. Using a deep-learning model, we propose an affordable, straightforward solution for classifying and detecting green and red crops. Ecuador, situated on the Equator in Latin America, boasts diverse climates and topographies, fostering a unique ecosystem conducive to the growth of various crops. Chili peppers, in particular, hold a significant position in short-cycle horticulture [25]. Ecuadorian farmers, especially those cultivating these pepper varieties, play a pivotal role in meeting their substantial demand. It's noteworthy that prior studies on chili peppers have often utilized datasets aimed at eliminating background noise or distractions to achieve higher accuracy. However, this approach may not be applicable in real-world scenarios where farms may present various natural conditions and obstacles, such as leaves, flowers, or other crops. Therefore, this convergence of technology and agriculture heralds a new era of heightened efficiency and accuracy in chili bell pepper production [26].

In the following subsection, we concisely review the recent advancements in machine learning and deep learning techniques used for crop classification, detection, and disease detection. We encompass a variety of fruits and vegetables, with particular attention given to chili peppers.

1-1- Related Work

Recent advancements in machine learning have significantly enhanced various agricultural tasks, primarily due to the adaptability provided by automatic feature extraction. For example, the study presented in Ekawaty et al. [27] addresses an analysis of the detection of cocoa. This study utilized a K-MEANS model and, based on the image capture distances, achieved accuracies of 93.3% at a distance of 50 cm, 64% at 100 cm, and 63% at 150 cm. In another study [28], the K-Nearest Neighbors (KNN) method was employed, using both Euclidean and Manhattan distance calculation algorithms to identify two types of features: color and shape. This method was used to classify five classes of chilies: cayenne pepper, green chili, big green chili, big red chili, and curly chili. The evaluation was conducted with 300 images. The classification method output yielded precision, recall, and accuracy values of 1.0.

Numerous studies have utilized deep learning algorithms to tackle various challenges in crop detection, classification, maturity estimation, and disease detection. For instance, Badeka et al. [14] applied YOLOv7-Tiny to estimate the maturity of grapes in 5 different stages, achieving an accuracy of 83.5%. This research utilized a dataset comprising 100 images captured weekly from the same fruit cluster. Another study presented in Pang & Chen [29] employed an alternative version to the traditional YOLOv5 model, named MS-YOLOv5, to detect the ripeness of strawberries, achieving an accuracy of 95.6%. This model replaces a layer of CNN inside YOLOv5 to enhance the classification of ripe and unripe strawberries. This approach was chosen due to the low precision achieved with the traditional model. A different case studied the same problem using cherry tomatoes [30]. This study utilized YOLOv7 to detect the maturity in clusters of the fruit, attaining an accuracy of 86.9%. They improved their results by modifying the loss function and testing it with their specific dataset.

Furthermore, while Han et al. [31] implemented YOLOv5 to estimate the maturity stage of tomatoes, achieving an accuracy of 92.77% on two classes, Yang et al. [32] utilized a MobileNet model adapted to the YOLOv5 algorithm to classify the growth period of tomatoes in three stages, obtaining an accuracy of 98%. On the other hand, Sun et al. [33] implemented another version of YOLO called YOLOv5-PRE, which is suitable for environments with significant background noise. They aimed to detect apple crops, and due to their distinct form and size, compared to branches and leaves in the background, they achieved an accuracy of 94.03%. Regarding apple diseases, the study of Alharbi and Arif [34] implemented CNN to detect and classify three different fungal diseases, such as apple scab, apple blotch, and apple rot, organized in groups of 800 pictures of each disease while also classifying healthy apples and achieving an accuracy of 99.17%. Many crops have garnered interest in training models for detection and classification, including lemons [35, 36], mushrooms [37, 38], and papaya [39, 40].

Regarding chili peppers, several machine-learning models have been tested. In the studies by Patil & Lad [19, 41], the authors employed ML-based classification techniques for disease detection in chili plant leaves. They utilized support vector machines and the k-nearest neighbor algorithm (KNN), showcasing varying efficiencies in disease detection and classification tasks on chili leaves. Both studies used RGB-format images to identify and classify five distinct chili leaf diseases. The Gray-Level Co-occurrence Matrix (GLCM) feature extraction technique was incorporated to enhance detection accuracy.

In the context of Sevilla et al. [38], the evaluation involved 704 images of the affected leaf dataset. The results revealed an accuracy of 83.33% with Support Vector Machines (SVM) and an impressive 93.00% with KNN. In Patil & Lad [41], the authors achieved an accuracy of 94.04% with SVM and 87.04% with KNN. The analysis encompassed testing 2500 samples. The review presented in Aminuddin et al. [42] explored the application of SVM and Random Forest (RF) as classifiers for discerning five distinct types of chili disease symptoms. These symptoms included spots, mottled mosaics, wrinkles, yellowed chili leaves, and folded veins. The study reported an overall accuracy of approximately 91% when employing these two techniques. Notably, the images in this research required feature extraction using deep learning techniques.

In the study by Tan et al. [43], an experiment was conducted to detect and classify diseases in chili plants, exploring the application of the RF algorithm [44]. The primary objective was to distinguish between healthy plants and four distinct classes of chili diseases, achieving an accuracy rate of 95%. The dataset, sourced from Kaggle, consists of 50 images per class, meticulously categorized into five classes. Another study on chili plant disease identification was undertaken by Islam et al. [22]. The study focused on distinguishing between weeds and crops through the utilization of RF, SVM, and KNN algorithms, yielding respective accuracy results of 96%, 94%, and 63%.

In advancing studies that utilized neural networks to implement deep learning, the study by Cruz-Domínguez et al. [45] introduced an innovative framework employing Artificial Neural Networks (ANNs) for classifying dried chili peppers (Capsicum annuum L.) based on their size and color. Utilizing 8-bit grayscale-image histograms for chili characterization, the system boasts an accuracy rate of 82.13%. This approach effectively mitigates the identification and classification challenges dehydrators and end customers face. The employed dataset comprises 850 isolated chili pepper samples. The capabilities of using CNNs are underscored in the study by Aldabbagh et al. [46], which explores the effectiveness of a deep learning algorithm in classifying images that portray distinct growth stages of chili plants. Despite utilizing a relatively small dataset of 256 photos, the Residual Network (ResNet)-101 and ResNet-50 models from the Faster Regions with Convolutional Neural Network-Mask (R-CNN) framework proved successful in discerning the age of chili plants. Notably, the Mask R-CNN ResNet-50 model achieved an impressive accuracy of 96%, albeit slightly outperformed by the Mask R-CNN ResNet-101 model. The dataset consisted of images captured from four chili plants, with each plant being photographed from both side and top views.

Expanding upon the potential of deep learning in chili farming, the study in Saad et al. [47] employs the R-CNN, a sophisticated deep learning model comprising approximately 177 layers. The model was trained on a diverse dataset comprising 500 multi-angle images of chili plants. The model achieved an Average Precision (AP) of 0.36 for chili detection and an even higher AP of 0.50 for chili flower detection. Thus, the Mean Average Precision (mAP) of the developed object detector is 43%. The relatively low mAP can be attributed to mislabeling objects in the training images.

The training dataset includes some chilies and chili flowers that are not entirely labeled. Given that AP calculations involve the overlap of detection, also known as Intersection over Union (IoU) of object detection ground truth, the inadequate labeling of ground truth contributes to the low mAP. Further reinforcing the utility of CNNs, the research in Purwaningsih et al. [48] implemented a CNN-based method, attaining a promising accuracy of 97.14% with the training data. Even when exposed to test data, the model exhibited robust performance, yielding an accuracy score of 80% when dealing with RGB input images. This model was explicitly used to categorize pictures of chilies into two groups: feasible and unfeasible for cultivation. The dataset comprised 80 images of individual red chili peppers against a white background.

In the realm of deep learning pre-trained models, particularly the YOLO model and its variants, several studies provide valuable insights into the growth stages of chili crops and facilitate the classification of different chili types. The study in Ram et al. [49] developed a red chili detection system using the YOLOv5 deep learning model compared with other object detection models, such as Faster R-CNN, Region-based Fully Conventional Networks (RFCN), and RetinaNet. The objective was to accurately identify ripened red chilies in real-world images. A customized dataset was created, consisting of pictures of red chilies from plants and individual chilies, totaling 1078 images. The system achieved 95% accuracy with YOLOv5.

Another study presented in Yin et al. [50] utilized YOLOv5 to distinguish between chili fruits and their leaves based on two characteristics: shape and color. A set of 391 images was generated to assess the model's ability to detect objects of various shapes and sizes. The YOLO and Mask R-CNN algorithms effectively solved object detection problems, achieving 78.2% and 95% precision, respectively. A 2D camera was used to capture 201 images of chilies in their plants under varying light intensity, viewing direction, and color (green, red, and brownish).

Furthermore, Mayalekshmi et al. [51] detected chili leaf diseases from images collected under actual field conditions using an RGB camera. The collected dataset consisted of 210 images. The YOLOv5 model correctly detected leaf spot and leaf curl classes with 40% and 57% accuracy, respectively. Overall, the model predicted the diseases with an accuracy of 75.64%. A more comprehensive set of classes using YOLOv5 was presented in Abubeker et al. [12], where an automated sorting system based on computer vision accurately identifies and classifies chilies based on attributes such as size, shape, color, and texture. The dataset for this research consists of images of bird-eye chilies in different positions and backgrounds. The chilies were then picked up by a robot manipulator and sorted by ripeness [52]. The system achieved a mAP of 0.94 and an average accuracy of 0.90 across a total of 1558 images.

In a separate study Ibrahim et al. [53], a YOLOv5 model was tested for detection and classification accuracy above 88%. The datasets, comprising 300 images from various categories such as green, red, and rotten chilies, were collected from 2D mobile device cameras. The chili fruits were photographed against a pure white background at various angles to provide sharp contrast and eliminate potential distractions. Zainudin et al. [54] applied YOLOv5 to identify chili's form and classification based on its color, using 56 sample images of chilies in single images and multiple colors. The precision for red chili was 93%, while for green chili, it was 73% in tested individual chilies. The second part of this study combined chili colors into the same image. The precision regarding classification in this case for red chili was 89%, while for green chili, it was 88%. In the case of chili prediction in a plant, the precision for red chili was 84%, while for green chili, it was 80%. Due to challenges in locating actual farms for experimentation, this study employed an artificial chili dataset with a white background to reduce noise and obstacles.

Regarding other versions of YOLO, the study of Tan et al. [55] utilized YOLOv4-tiny with 85% precision and YOLOv4 + Mosaic + Convolutional Block Attention Module (CBAM) with data augmentation to achieve 100% precision. A total of 500 images of peppers in a natural light environment were collected with an industrial Hikvision camera, and different pepper plants were photographed from various angles during the collection process.

Another study conducted by Hespeler et al. [56] collected RGB and thermal images of chili peppers in an environment of multiple amounts of debris, pepper overlapping, and ambient lighting, obtaining a mAP of 0.97 using YOLOv3. Further extending the applicability of the YOLO algorithm, the study in Manan et al. [57] utilized the YOLO Darknet detector to identify chili and its leaves within chili plant images. This contributes to robotic vision and growth monitoring, improving productivity and quality. The algorithm was applied to an augmented dataset of 1866 images of bird's eye chili and its leaves.

Compared with other transfer learning models such as YOLO Tiny, Faster R-CNN, and EfficientDet, the YOLOv4 Darknet model emerged as the most accurate, achieving a mAP of 75.69%. Finally, Sudianto et al. [58] utilized a dataset containing 100 photos with 50 pictures of "quality A" chilies and 50 photos of "quality B" chilies to train a YOLOv3 model. The accuracy obtained at iteration 9000 yielded an average accuracy of 75.6%. This model was trained using individual red chili peppers on a white background.

To summarize, Table 1 presents a concise description of the research focused on chili peppers and plants using YOLO, along with the contribution of this paper.

Table 1. State of the art YOLO models applied to chili plants

Author	Year	Problem Definition	Targeted Crop	Dataset	Model	Results
Ram et al. [49]	2023	Crop detection	Red Chili peppers	Individual chilies and plants	YOLOv5	Detection Accuracy: 95%
Yin et al. [50]	2023	Crop detection and classification	Ghost pepper and cili padi	Pictures of chilies in plants	YOLOv5	Detection Precision: 78.2% Classification Precision: 90%
Mayalekshmi et al. [51]	2023	Leaf disease	Red chili leaf	RGB Images from chili field	YOLOv5	Detection Accuracy: 75.64%
Abubeker et al. [52]	2023	Crop detection and classification	Bird eye chili	Pictures from chili farm	YOLOv5	Detection Accuracy: Red Chili: 92.79% Green Chili: 93.46% Classification Accuracy: 90%
Ibrahim et al. [53]	2023	Crop detection and classification	Green, red and rotten chili	Chili plant pictures	YOLOv5	Detection Precision: 90% Classification Precision: 88%
Tan et al. [55]	2023	Crop Detection	Chili pepper	Chili plant pictures	YOLOv4	Detection Precision: 85%
Zainudin et al. [54]	2022	Crop detection and classification	Red and green chili	Pictures of artificial chilies and plants	YOLOv5	Detection Precision: Red Chili: 84% Green Chili: 80% Classification Precision: 90%
Hespeler et al [56]	2021	Crop detection	Red chili	RGB and Thermal Images	YOLOv3	Detection mAP: 97%
Manan A. et al. [57]	2020	Crop and leaf detection	Bird's eye chili	Images of leaves and chili crops	YOLOv4	Detection mAP: 75.69%
Sudianto et al. [58]	2020	Crop quality classification	Chili pepper	Individuals Chili peppers	YOLOv3	Classification Accuracy: 75.6%
Proposal	2024	Crop Detection and Classification	Red and Green Chili Pepper	Pictures of chili plants in natural environment like rocoto red and green chili	YOLOv5	Detection Accuracy: 84.4% Classification Accuracy: 99.9%

1-2- Main Contribution

As evidenced by the current state of the art, numerous studies have been conducted on classifying and detecting chili peppers. This project, however, introduces unique contributions to detecting the maturity stage of the "rocoto" chili pepper cultivated in Ecuador.

- Previous studies predominantly utilized images of individual chilies or plants under ideal lighting conditions, with white backgrounds or clearly visible chilies without obstacles. In contrast, this work introduces a novel dataset divided into two primary categories: red-chili and green-chili. The uniqueness of this dataset lies in its high-fidelity representation of chilies in their natural environment. Rather than isolating the chili peppers, images captured the entire plant during various stages, from planting to harvesting. This includes the presence of potentially confounding elements such as other plants (roses), leaves, and other parts of the plant. By intentionally avoiding special lighting conditions and preserving the plant's natural state, the dataset provides a more challenging yet realistic environment for model training.
- Multiple training sessions were conducted under varying hyper-parameters and model sizes to optimize the results for our dataset. The presented methodology employed both the original dataset and an augmented version. Additionally, various tests were conducted with different sizes of the YOLO model and varying hyperparameters to better understand how each value influences the results.
- The study identified a model using YOLOv5 in its nano size, with finely tuned training hyperparameters of epochs, optimizer, and batch size. This model achieved a classification accuracy of 99.9% and a detection accuracy of 84%. When tested in a real scenario, the model demonstrated high accuracy and precision, even considering other plants' presence and the crops' obstruction by leaves. The high accuracy achieved, given the images present in the dataset, underscores the robustness and effectiveness of the model.

1-3- Outline

This work is organized as follows: Section 2 presents the methodology used. Section 3 details the results obtained from the model using the given dataset, including experimental, validation, and testing outcomes. Section 4 presents the Discussion. Finally, the conclusions are presented in Section 5.

2- Research Methodology

This section details the methodology adopted for this study, providing a comprehensive explanation of the processes and approaches implemented. The overall methodology pipeline, as illustrated in Figure 1, visually represents the steps and techniques employed throughout this research.

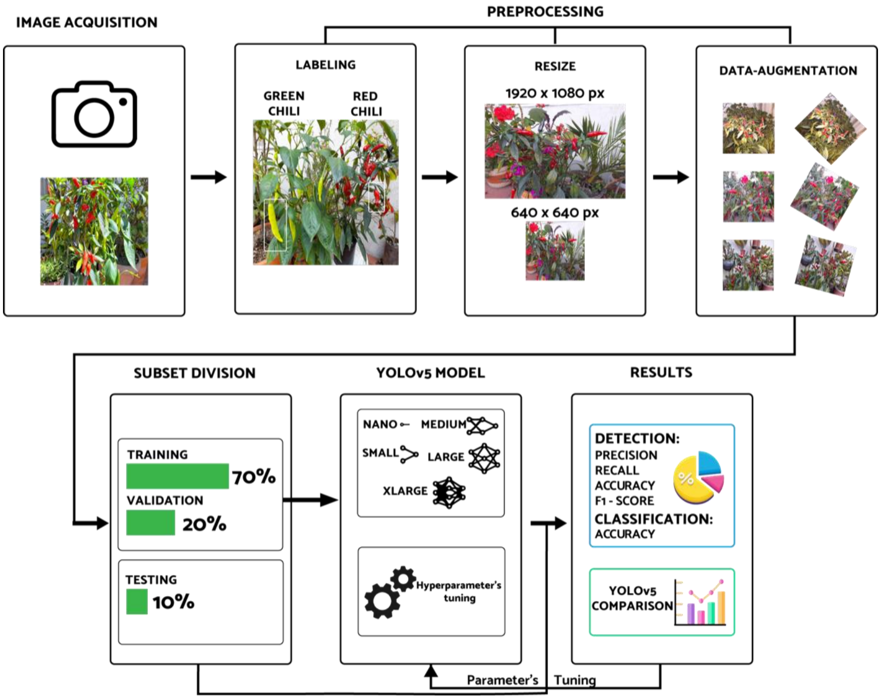

Figure 1. Proposed Architecture for Chili Crop Detection and Maturity Classification Using a YOLOv5-Based Image Analysis

2-1- Data Acquisition

In Ecuador, chili plants exhibit a wide range of species and are primarily found in hotter regions. The chili varieties present in Ecuador include pancha, chipotle, ancho, peruvian chili, cherry, rocoto, habanero, yellow banana, dandelion, and rooster's foot. For training, validating, and testing the YOLOv5 model, a dataset was compiled using images of rocoto chili plants from a small orchard. This location was chosen due to the vast array of chili colors available primarily green and red. Figure 2 showcases a sample from the curated database, illustrating the various scenarios in which chili peppers are found. The dataset comprises 1203 images, captured with a 20MP cellphone camera at a resolution of 1920×1080 pixels.

Figure 2. Developed Database Characteristics and Sample Images

The dataset images depict chilies in their natural state, captured from various angles and positions. They were photographed in natural light and background conditions, without being harvested, providing a wide range of scenarios. These conditions facilitated the training of the model and its testing against most of the challenges it would encounter in a real-world application. These challenges include leaf obstructions, varying environmental lighting, and plants bearing many fruits in red and green stages.

2-2- Data Labelling, Preprocessing and Augmentation

Once all pictures of the dataset were collected, they were uploaded to Roboflow for labeling and classification into subsets for training, validation, and testing. Each photo was manually labeled using Roboflow's tool to encompass each chili in the images with bounding boxes corresponding to their respective classes. Because our native language is Spanish, the classes assigned to each chili correspond to its names in that language. Once all crops were assigned a bounding box, they were converted to a resolution of 640×640 pixels to reduce training time and to adapt them to the YOLOv5 requirements. Then, two versions of the dataset were generated. The first version consists of only the original pictures labeled and assigned to training, validation, and testing. A second version was later compiled to include data augmentation consisting of rotated versions of the original pictures, resulting in a total of 2881 images. The distribution of both datasets, as well as the labels used for this study, are detailed in Table 2.

Table 2. Dataset information

Category	Images	
Training (70%)	841 images (without augmentation)	2519 images (with augmentation)
Validation (20%)	243 images	
Testing (10%)	119 images	
Labels	**Meaning**	
aji-rojo	Red chili	
aji-verde	Green chili	

2-3- Model Architecture

This work utilizes the standard YOLOv5 network architecture delineated in Figure 3. It is structured into three primary segments: the backbone, the neck, and the head.

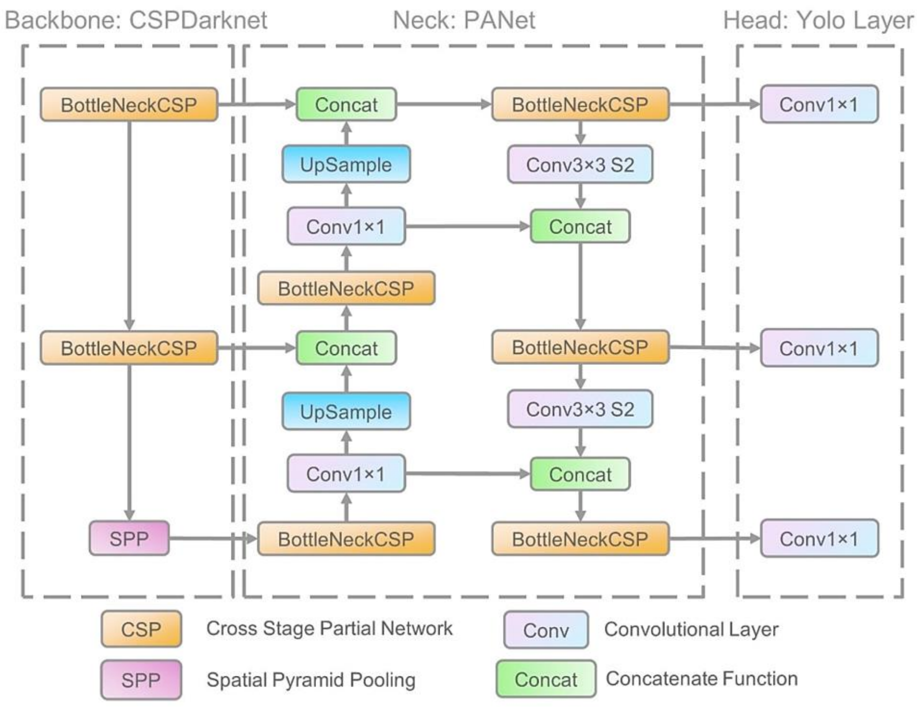

Figure 3. Architecture Developed for Chili Plant [59]

Within this structure, YOLOv5 integrates the cross-stage partial network (CSPNet) [60] with Darknet, resulting in the creation of the CSPDarknet backbone. Initially, the data is processed by CSPDarknet for feature extraction. This is followed by the path aggregation network (PANet), which merges the data before the YOLO layer generates the detection results. Incorporating PANet [61] is a strategic bottleneck in YOLOv5, enhancing data throughput. It includes a novel feature pyramid network (FPN) topology strengthened by an advanced bottom-up pathway, which enhances low-level feature propagation. Through this, PANet not only enhances the precise localization signals in the lower layers but also improves object location accuracy. Lastly, the head of YOLOv5, specifically the YOLO layer, generates feature maps in three distinct sizes (18×18, 36×36, and 72×72), enabling multi-scale [62] prediction. This versatility empowers the model to effectively handle objects of varying sizes, from small to large.

In the present study, although the pictures were taken using a 20MP and had a resolution of 1920x1080 pixels, the images were resized to adjust to the standard 640x640 resolution input for YOLOv5. We aimed to test all sizes of the YOLOv5 model (nano, small, medium, large, and extra-large). However, due to hardware limitations encountered during training, we ran out of GPU memory with the large and extra-large models. Additionally, the medium-sized model did not provide any difference in results obtained compared to the two smaller models and took too much time to train, rendering it unsuitable for the requirement.

2-4- Training

A testing environment was implemented once the datasets were defined and correctly labeled. Initially, we conducted preliminary training tests on a medium-high-end computer. However, we encountered issues such as prolonged training times, overheating of hardware components, and errors during the training process, which hindered accurate results. Subsequently, the training environment was transitioned to a Google Colab virtual machine with enhanced computational resources. A comparison of the hardware utilized in this study is presented in Table 3.

Table 3. Training Environments

Environment	Component	Capacity
Computer with AMD Ryzen 7-5800H CPU	RAM	16 GB
	GPU	RTX 3050 4 GB VRAM
Google Colab Pro Environment	RAM	12.7 GB
	GPU	T4 GPU 15 GB VRAM

In pursuit of optimal accuracy in the detection and classification of both green and red chili peppers, a variety of training variations were implemented. The specific parameters utilized during the training phase are outlined in Table 4.

Table 4. Training Parameters

Parameter	Value
Dataset	Without Augmentation – 1203 images With Augmentation – 2881 images
Model Size	YOLOv5 Nano – 1.9 M parameters YOLOv5 Small – 7.2 M parameters YOLOv5 Medium – 21.2 M Parameters (Training time too long) YOLOv5 Large – 46.5 M Parameters (Out of GPU memory) VOLOv5 Extra Large – 86.7 M Parameters (Out of GPU memory)
Epochs	25 50 75 100
Optimizer	Stochastic Gradient Descent (SGD) Adaptive Moment Estimation (Adam) Adaptive Moment Estimation with Weight Decay (AdamW)
Batch Size	16 32 64 128
Starting Weights	YOLOv5 Default
Number of Classes	2
Learning Rate	Automatically adjusted by model

The relevant metrics for detection and classification were obtained for each trained variation and will be presented in the following section.

3- Experiments and Results

In this section, we present the results of the various trained variations. We utilize metrics such as recall, precision, accuracy, and the F1 score to ensure a fair comparison among the obtained results. It is important to note that this study aims to train a model for two tasks: detecting a chili pepper of either of the pre-defined classes within an image of a chili plant and classifying it into the green and red variants.

The metrics used are mathematically described in Equations 1 to 4 provided by Aishwarya et al. [63], where TP, FP, TN, and FN represent true positives, false positives, true negatives, and false negatives, respectively. This measurement helps ascertain the proportion of positive identifications that were indeed correct.

$$Recall = \frac{TP}{(TP+FN)} \tag{1}$$

$$Precision = \frac{TP}{(TP+FP)} \tag{2}$$

$$Accuracy = \frac{TP+TN}{(TP+TN+FP+FN)} \tag{3}$$

$$F1score = \frac{2(Precision\ x\ Recall)}{(Precision + Recall)} \tag{4}$$

For the detection task, we present all four metrics for the detection task as it is where the model faced the most challenges. The dataset nature caused difficulties as the chili peppers were often partially obstructed by the plant, flowers, background, other chili peppers, and especially the leaves. The leaves have a strong resemblance to the peppers, making it harder for the model to differentiate between the two. Regarding classification, all models achieved accuracy scores between 99% and 100%, resulting in all other metrics also scoring 100%.

3-1- Validation Results

In the process of optimizing the model during training, a validation dataset comprising 243 images was utilized. Table 5 presents each trained variation along with its corresponding metrics and highlights the best model identified.

Table 5. Validation Results

Dataset Variation - Model's default values given by Ultralytics								
Dataset	**Class**	**Detection Matrix**		**Precision**	**Recall**	**Accuracy**	**F1 Score**	**Classification Accuracy**
Without Augmentation	Red	0.73	0.22	76.84%	73.00%	75.50%	74.87%	100.00%
	Green	0.27	0.78	74.29%	78.00%		76.10%	100.00%
With Augmentation	Red	0.8	0.21	79.21%	80.00%	79.50%	79.60%	100.00%
	Green	0.2	0.79	79.80%	79.00%		79.40%	100.00%
Best Result: Dataset with Augmentation								
Model	**Class**	**Detection Matrix**		**Precision**	**Recall**	**Accuracy**	**F1 Score**	**Classification Accuracy**
YOLOv5 nano	Red	0.82	0.2	80.39%	82.00%	81.00%	81.19%	100.00%
	Green	0.18	0.8	81.63%	80.00%		80.81%	100.00%
YOLOv5 small	Red	0.8	0.21	79.21%	80.00%	79.50%	79.60%	100.00%
	Green	0.2	0.79	79.80%	79.00%		79.40%	100.00%
Best Result: YOLOv5 nano								
Epochs	**Class**	**Detection Matrix**		**Precision**	**Recall**	**Accuracy**	**F1 Score**	**Classification Accuracy**
25	Red	0.79	0.25	75.96%	79.00%	77.00%	77.45%	100.00%
	Green	0.21	0.75	78.13%	75.00%		76.53%	100.00%
50	Red	0.83	0.2	80.58%	83.00%	81.50%	81.77%	100.00%
	Green	0.17	0.8	82.47%	80.00%		81.22%	100.00%
75	Red	0.83	0.17	83.00%	83.00%	83.00%	83.00%	100.00%
	Green	0.17	0.83	83.00%	83.00%		83.00%	100.00%
100	Red	0.82	0.19	81.19%	82.00%	81.41%	81.59%	100.00%
	Green	0.18	0.8	81.63%	80.81%		81.22%	99.00%
Best Result: 75 Epochs								
Optimizer	**Class**	**Detection Matrix**		**Precision**	**Recall**	**Accuracy**	**F1 Score**	**Classification Accuracy**
SGD	Red	0.83	0.17	83.00%	83.00%	83.00%	83.00%	100.00%
	Green	0.17	0.83	83.00%	83.00%		83.00%	100.00%
ADAM	Red	0.78	0.31	71.56%	78.00%	73.50%	74.64%	100.00%
	Green	0.22	0.69	75.82%	69.00%		72.25%	100.00%
ADAMW	Red	0.82	0.18	82.00%	82.00%	81.91%	82.00%	100.00%
	Green	0.18	0.81	81.82%	81.82%		81.82%	99.00%

Best Result: SGD Optimizer								
Batch Size	**Class**	**Detection Matrix**		**Precision**	**Recall**	**Accuracy**	**F1 Score**	**Classification Accuracy**
16	Red	0.82	0.2	80.39%	82.00%	81.00%	81.19%	100.00%
	Green	0.18	0.8	81.63%	80.00%		80.81%	100.00%
32	Red	0.82	0.18	82.00%	82.00%	81.91%	82.00%	100.00%
	Green	0.18	0.81	81.82%	81.82%		81.82%	99.00%
64	**Red**	**0.83**	**0.17**	**83.00%**	**83.00%**	**83.00%**	**83.00%**	**100.00%**
	Green	**0.17**	**0.83**	**83.00%**	**83.00%**		**83.00%**	**100.00%**
128	Red	0.81	0.18	81.82%	81.00%	81.50%	81.41%	100.00%
	Green	0.19	0.82	81.19%	82.00%		81.59%	100.00%
Best Result: Batch size 64								
Selected Model: YOLOv5 nano, 75 epochs, SGD optimizer, 64 Batch Size								

Through various parameter combinations, as shown in Table 5, this paper unveils a model that effectively minimizes errors during the validation phase. This model comprises a YOLOv5 nano trained with the data-augmented dataset in 75 epochs, optimized using SGD, with a batch size of 64.

Notably, this model not only performed well on the validation dataset but also exhibited proficiency in accurately distinguishing between red and green chilies when tested on a separate dataset, distinct from the one used for training.

3-2- Testing Results

Utilizing the model discovered during the training and validation phases, an example of the model in action is shown in Figure 4. This illustration highlights the model's capability to identify and locate objects (chili peppers) within the plant. It achieves this by enclosing the chili in a bounding rectangle and providing a corresponding color label. Subsequently, in Figure 5, we progress to the next prediction phase. Here, the system not only furnishes the user with the precise location and classification of the chili fruit but also offers a trust threshold, thereby enhancing the depth of information provided.

Figure 4. Sample of location and classification of chili peppers during the testing phase

(a) Red Chili Predictions (b) Green Chili Predictions

(c) Red and Green Chili Predictions (d) Red and Green Chili Predictions.

Figure 5. Prediction accuracy of green chili peppers (shown as aji-verde) is distinguishable from red species (labeled as aji-rojo

As observed, when presented with previously unseen images, the model effectively detects and classifies chili peppers despite encountering obstacles such as leaves owing to using a sophisticated dataset for training and validation.

However, the model encounters specific challenges stemming from the close resemblance between green chili fruits and the plant's leaves and stems. This leads to occasional difficulty in achieving 100% precise recognition in real-world scenarios. Furthermore, detecting red chilies may face hurdles, particularly when confronted with similarly colored objects like red roses in the background. These challenges contribute to an overall detection precision of 85.57% for red chilies and 83,33% for green chilies. Other contributing factors to these limitations include the positioning of chili fruits, image distortions, and the physical attributes of the leaves. As part of our result analysis, we present the confusion matrix for depicted in Figure 6 for a testing run consisting of 119 pictures.

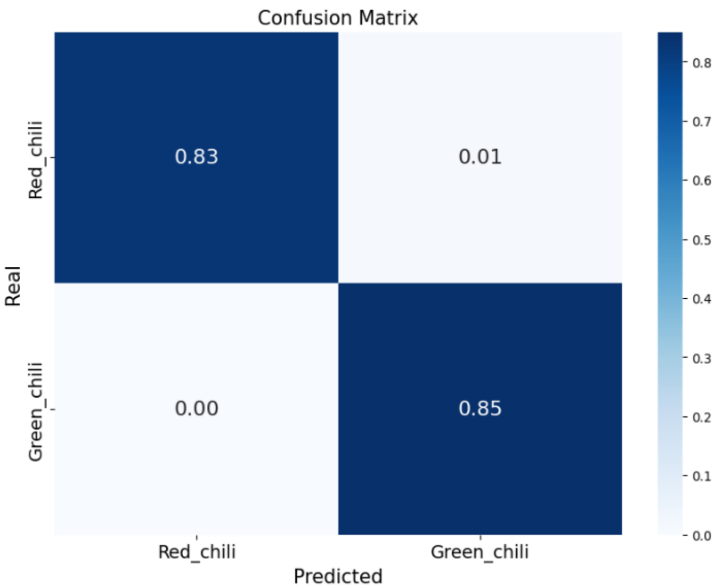

Figure 6. Confusion matrix of the testing results

It is important to note that, in this case, the matrix addresses the detection task, as the classification accuracy for both classes is 99.99%.

The confusion matrix provides crucial metrics such as TP, FP, TN, and FN. In this context, an analysis of these evaluation parameters through the confusion matrix reveals the outcomes within both the testing and validation datasets, as presented in Table 6. The model demonstrates commendable balance in the testing set, achieving an average of 84% for recall, precision, and F1 score for the detection task, with 84.4% accuracy. On the other hand, the results for the classification task demonstrate exceptional performance, with recall, precision, accuracy, and the F1 score all-surpassing 99%; these results emphasize the model's versatility and suitability, demonstrating its proficiency in both datasets while also highlighting the potential for improvement, particularly in enhancing recall and precision for testing scenarios.

Table 6. Validation and Testing Results

Metrics	Validation		Testing	
	Detection	Classification	Detection	Classification
Precision	83%	100%	Red: 85.57% | Green: 83.33%	99.9%
Recall	83%	100%	Red: 83% | Green: 85.86%	99.9%
Accuracy	83%	100%	84.42%	99.9%
F1score	83%	100%	Red: 84.26% | Green: 84.58%	99.9%

Figure 7 illustrates the plots of various metrics obtained using the testing dataset, including the Recall Confidence Curve, the F1 Confidence Curve, the Precision Confidence Curve, and the Precision-Recall Curve.

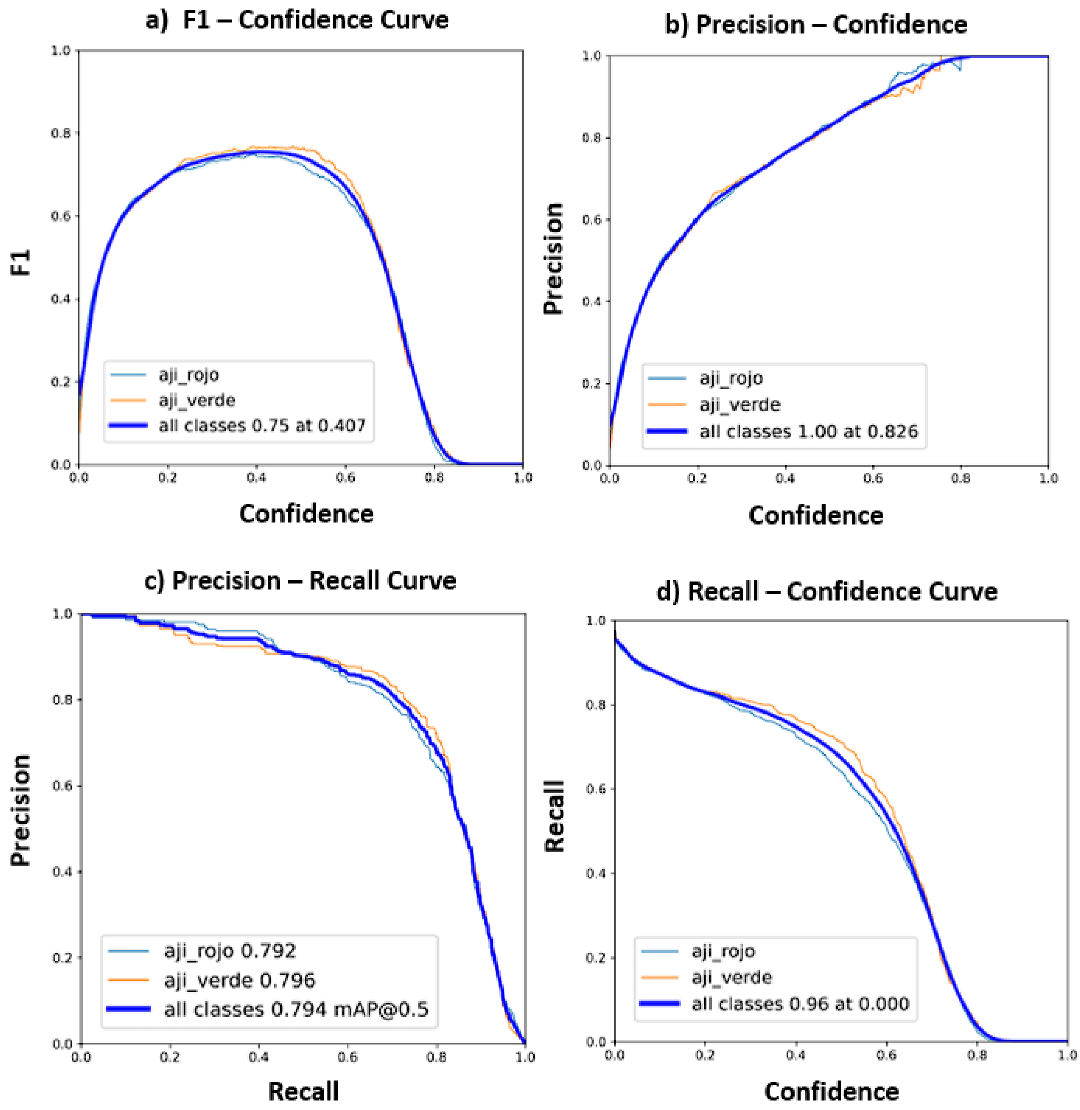

Figure 7. a) F1 Confidence Curve, b) Precision Confidence Curve, c) Precision Recall Curve, and d) Recall-Confidence Curve for testing results

4- Discussion

- This study focuses on detecting and classifying chili peppers cultivated in Ecuador. To achieve this, we created a novel dataset under real-world conditions and explored various combinations to optimize results. The selected model was trained with 2881 images, employing a YOLO V5n model over 75 epochs with a batch size of 64. Notably, the most favorable outcomes were achieved using the YOLOv5 nano with 1.9 trainable parameters. This compact size allows easy implementation on small hardware while maintaining commendable performance and swift inference times, owing to the task's simplicity. Although tests were conducted with larger models, like the YOLOv5 medium, no significant improvements in metrics were observed. This could be attributed to the increased complexity introduced by a higher number of parameters, making it challenging to extract pertinent features for a relatively straightforward task. Consequently, this compromises the model’s ability to produce accurate results.

- In the state of the art, three studies offer points of comparison with the approach proposed in this work, focusing on detection and classification [50, 52, 54], as presented in Table 7. The works by Yin et al. [50] and Abubeker et al. [52] utilize images where the chili peppers are unobstructed by leaves or branches. In Abubeker et al. [52], their model operates within an automated machine tasked with harvesting chilies, resulting in peppers positioned outside the plant, facilitating easier identification. Conversely, Zainudin et al. [54] developed a dataset within a controlled environment using an artificial plant, with images captured against a white background. Previous detection studies involving chili plants typically create datasets within obstacle-free environments [50]. In contrast, the dataset we used to train the network encompasses various obstacles and lacks lighting control. Despite these challenges, the model achieves a detection accuracy of 84.4% and a classification accuracy of 99.9%.

Table 7. **Comparison with Others Research**

Research	Detection	Classification
Yin et al. [50]	Precision: 78.2%	Precision: 90%
Abubeker et al. [52]	Red Chili Accuracy: 92.79% Green Chili Accuracy: 93.46%	Accuracy: 90%
Shah et al. [54]	Red Chili Precision: 84% Green Chili Precision: 80%	Precision: 90%
Proposal	Red Precision: 85.57% Green Precision: 83.33%	Precision 99.9%

- In future research, we propose to comprehensively explore various methods to optimize the YOLO model's specific characteristics. This exploration involves a detailed analysis of feature enhancement techniques, including the use of pre-trained models, the addition of additional convolutional layers, hyperparameter tuning, the use of data augmentation techniques, and the expansion of normalization layers. Additionally, it is suggested that a complete comparison with other well-known object detectors, such as Faster RCNN and Single Shot Multibox Detector (SSD), be performed to obtain a more complete perspective of the model's performance. This comparison will provide a deeper understanding of each approach's relative strengths and weaknesses, generating valuable information that will support model selection and improvement in future research.

5- Conclusion

This study presents a comparative analysis of training a YOLOv5 model under different dataset conditions, sizes, and parameter configurations, particularly optimizing hyperparameters for detecting and classifying red and green rocoto chili peppers cultivated in Ecuador. The main objective of this research is to develop a model capable of identifying plants in their natural state without requiring any special treatment of the plant or pepper. This aspect provides a valuable tool for small-scale farmers, as they can classify and detect peppers without removing them from the plant, enabling field use without additional adaptations. Remarkably, the model’s performance in the classification task consistently surpasses a 99.9% accuracy threshold. This level of accuracy illustrates the model's capability to accurately differentiate between red and green chiles, even in challenging natural settings characterized by limited visibility or adverse lighting conditions. Furthermore, the model has demonstrated its efficacy in detecting chili peppers on plants regardless of obstacles, with an accuracy rate exceeding 84%.

It is fundamental to highlight that these results are attained without requiring plant manipulation during the classification process. Image noise, including leaves, branches, and other plants, represents an additional challenge for the model. Nonetheless, the results demonstrate the model's remarkable capability to accurately identify red and green chili peppers despite these interferences, with short inference times and without the need for expensive hardware. Consequently, this study establishes a promising precedent for future plant detection and classification research employing artificial intelligence.

6- Declarations

6-1- Author Contributions

Conceptualization, V.M. and A.Q.; methodology, V.M.; software, V.M. and C.V.; validation, V.M, J.V., and A.P.; formal analysis, V.M.; investigation, V.M.; resources, A.Q. and A.P.; data curation, A.P.; writing—original draft preparation, V.M.; writing—review and editing, A.Q., J.V., and A.P.; visualization, V.M.; supervision, J.V.; project administration, A.P.; funding acquisition, J.V. All authors have read and agreed to the published version of the manuscript.

6-2- Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6-3- Funding

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6-4- Institutional Review Board Statement

Not applicable.

6-5- Informed Consent Statement

Not applicable.

6-6- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

7- References

[1] Hou, X., Li, J., Yin, S., & Yuan, H. (2022). Evolution of Agricultural Innovation Ecosystem in County Areas: A Life-Cycle Perspective of Cases in Hebei Province. Mathematical Problems in Engineering, 2022, 1–21. doi:10.1155/2022/5262248.

[2] Godfray, H. C. J., Crute, I. R., Haddad, L., Muir, J. F., Nisbett, N., Lawrence, D., Pretty, J., Robinson, S., Toulmin, C., & Whiteley, R. (2010). The future of the global food system. Philosophical Transactions of the Royal Society B: Biological Sciences, 365(1554), 2769–2777. doi:10.1098/rstb.2010.0180.

[3] Durán, Y., Gómez-Valenzuela, V., & Ramírez, K. (2023). Socio-technical transitions and sustainable agriculture in Latin America and the Caribbean: a systematic review of the literature 2010–2021. Frontiers in Sustainable Food Systems, 7, 1-13. doi:10.3389/fsufs.2023.1145263.

[4] Sharma, R. (2021). Artificial Intelligence in Agriculture: A Review. 2021 5th International Conference on Intelligent Computing and Control Systems (ICICCS), Madurai, India. doi:10.1109/iciccs51141.2021.9432187.

[5] Li, J., Chen, D., Qi, X., Li, Z., Huang, Y., Morris, D., & Tan, X. (2023). Label-efficient learning in agriculture: A comprehensive review. Computers and Electronics in Agriculture, 215, 108412. doi:10.1016/j.compag.2023.108412.

[6] Bharman, P., Ahmad Saad, S., Khan, S., Jahan, I., Ray, M., & Biswas, M. (2022). Deep Learning in Agriculture: A Review. Asian Journal of Research in Computer Science, 13(2), 28–47. doi:10.9734/ajrcos/2022/v13i230311.

[7] Benos, L., Tagarakis, A. C., Dolias, G., Berruto, R., Kateris, D., & Bochtis, D. (2021). Machine learning in agriculture: A comprehensive updated review. Sensors, 21(11), 3758. doi:10.3390/s21113758.

[8] Mukhiddinov, M., Muminov, A., & Cho, J. (2022). Improved Classification Approach for Fruits and Vegetables Freshness Based on Deep Learning. Sensors, 22(21), 8192. doi:10.3390/s22218192.

[9] Dubey, S. R., & Jalal, A. S. (2013). Species and variety detection of fruits and vegetables from images. International Journal of Applied Pattern Recognition, 1(1), 108. doi:10.1504/ijapr.2013.052343.

[10] Tripathi, M. K., & Maktedar, D. D. (2021). Detection of various categories of fruits and vegetables through various descriptors using machine learning techniques. International Journal of Computational Intelligence Studies, 10(1), 36. doi:10.1504/ijcistudies.2021.113819.

[11] Rahmadian, R., & Widyartono, M. (2020). Autonomous Robotic in Agriculture: A Review. 2020 Third International Conference on Vocational Education and Electrical Engineering (ICVEE), Surabaya, Indonesia. doi:10.1109/icvee50212.2020.9243253.

[12] Abubeker, K. M., Akhil, S., VK, A. K., & Jose, B. K. (2023). Computer Vision Assisted Real-Time Bird Eye Chili Classification Using YOLO V5 Framework. Journal of Artificial Intelligence and Technology, 1-13. doi:10.37965/jait.2023.0251.

[13] Habib, Md. T., Raza, D. M., Islam, Md. M., Victor, D. B., & Arif, Md. A. I. (2022). Applications of Computer Vision and Machine Learning in Agriculture: A State-of-the-Art Glimpse. 2022 International Conference on Innovative Trends in Information Technology (ICITIIT). doi:10.1109/icitiit54346.2022.9744150.

[14] Badeka, E., Karapatzak, E., Karampatea, A., Bouloumpasi, E., Kalathas, I., Lytridis, C., Tziolas, E., Tsakalidou, V. N., & Kaburlasos, V. G. (2023). A Deep Learning Approach for Precision Viticulture, Assessing Grape Maturity via YOLOv7. Sensors, 23(19). doi:10.3390/s23198126.

[15] Jiang, P., Ergu, D., Liu, F., Cai, Y., & Ma, B. (2022). A Review of Yolo Algorithm Developments. Procedia Computer Science, 199, 1066–1073. doi:10.1016/j.procs.2022.01.135.

[16] Li, Y., Feng, X., Liu, Y., & Han, X. (2021). Apple quality identification and classification by image processing based on convolutional neural networks. Scientific Reports, 11(1), 16618. doi:10.1038/s41598-021-96103-2.

[17] Xuan, G., Gao, C., Shao, Y., Zhang, M., Wang, Y., Zhong, J., Li, Q., & Peng, H. (2020). Apple Detection in Natural Environment Using Deep Learning Algorithms. IEEE Access, 8, 216772–216780. doi:10.1109/ACCESS.2020.3040423.

[18] Xiao, J.-R., Chung, P.-C., Wu, H.-Y., Phan, Q.-H., Yeh, J.-L. A., & Hou, M. T.-K. (2020). Detection of Strawberry Diseases Using a Convolutional Neural Network. Plants, 10(1), 31. doi:10.3390/plants10010031.

[19] Patil, A., & Lad, K. (2021). Chili Plant Leaf Disease Detection Using SVM and KNN Classification. Rising Threats in Expert Applications and Solutions. Advances in Intelligent Systems and Computing, 1187. Springer, Singapore. doi:10.1007/978-981-15-6014-9_26.

[20] Khalid, M., Sarfraz, M. S., Iqbal, U., Aftab, M. U., Niedbała, G., & Rauf, H. T. (2023). Real-Time Plant Health Detection Using Deep Convolutional Neural Networks. Agriculture (Switzerland), 13(2), 2–16. doi:10.3390/agriculture13020510.

[21] Ahmad, A., Saraswat, D., & El Gamal, A. (2023). A survey on using deep learning techniques for plant disease diagnosis and recommendations for development of appropriate tools. Smart Agricultural Technology, 3, 2772–3775. doi:10.1016/j.atech.2022.100083.

[22] Islam, N., Rashid, M. M., Wibowo, S., Xu, C. Y., Morshed, A., Wasimi, S. A., Moore, S., & Rahman, S. M. (2021). Early weed detection using image processing and machine learning techniques in an Australian Chilli farm. Agriculture (Switzerland), 11(5), 1–13. doi:10.3390/agriculture11050387.

[23] Manish Lad, A., Mani Bharathi, K., Akash Saravanan, B., & Karthik, R. (2022). Factors affecting agriculture and estimation of crop yield using supervised learning algorithms. Materials Today: Proceedings, 62(7), 4629–4634. doi:10.1016/j.matpr.2022.03.080.

[24] Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. Computers and Electronics in Agriculture, 147, 70–90. doi:10.1016/j.compag.2018.02.016.

[25] Solis-Charcopa, K. F., Quiroz-Ponce, F., Vernaza-Quiñonez, L. M., & Carrera-Villacrés, F. (2017). Biofertilizers an ecological alternative for agriculture in the face of climate change in Ecuador. Dominio de Las Ciencias, 3(4), 75–88. doi:10.23857/DOM.CIEN.POCAIP.2017.3.4.OCT.75-88. (In Spanish).

[26] Jacob, A., Edward, E. O., & Yaw, B. O. A. (2016). Efficiency of chili pepper production in the Volta region of Ghana. Journal of Agricultural Extension and Rural Development, 8(6), 99–110. doi:10.5897/jaerd2016.0765.

[27] Ekawaty, Y., Indrabayu, & Areni, I. S. (2019). Automatic Cacao Pod Detection under Outdoor Condition Using Computer Vision. 2019 4th International Conference on Information Technology, Information Systems and Electrical Engineering (ICITISEE). doi:10.1109/icitisee48480.2019.9003733.

[28] Sihombing, Y. F., Septiarini, A., Kridalaksana, A. H., & Puspitasari, N. (2022). Chili Classification Using Shape and Color Features Based on Image Processing. Scientific Journal of Informatics, 9(1), 42–50. doi:10.15294/sji.v9i1.33658.

[29] Pang, F., & Chen, X. (2023). MS-YOLOv5: a lightweight algorithm for strawberry ripeness detection based on deep learning. Systems Science & Control Engineering, 11(1), 1–11. doi:10.1080/21642583.2023.2285292.

[30] Liu, M., Wang, Y., Li, X., Han, W., & Chen, W. (2023). Multi-task Tomato Fruit and Bunch Maturity Detection Approach Based on Improved YOLOv7. 2023 IEEE 9th International Conference on Cloud Computing and Intelligent Systems (CCIS), Dali, China. doi:10.1109/ccis59572.2023.10262866.

[31] Han, W., Hao, W., Sun, J., Xue, Y., & Li, W. (2022). Tomatoes Maturity Detection Approach Based on YOLOv5 and Attention Mechanisms. 2022 IEEE 4th International Conference on Civil Aviation Safety and Information Technology (ICCASIT), Dali, China. doi:10.1109/iccasit55263.2022.9986640.

[32] Yang, Y., Han, Y., Li, S., Li, H., & Zhang, M. (2022). Multi-Growth Period Tomato Fruit Detection Using Improved Yolov5. International Journal of Robotics and Automation Technology, 9, 44–55. doi:10.31875/2409-9694.2022.09.06.

[33] Sun, L., Hu, G., Chen, C., Cai, H., Li, C., Zhang, S., & Chen, J. (2022). Lightweight Apple Detection in Complex Orchards Using YOLOV5-PRE. Horticulturae, 8(12), 1–15. doi:10.3390/horticulturae8121169.

[34] Alharbi, A. G., & Arif, M. (2020). Detection And Classification of Apple Diseases using Convolutional Neural Networks. 2020 2nd International Conference on Computer and Information Sciences (ICCIS), Sakaka, Saudi Arabia. doi:10.1109/iccis49240.2020.9257640.

[35] Sharma, R., & Kukreja, V. (2022). Amalgamated convolutional long term network (CLTN) model for Lemon Citrus Canker Disease Multi-classification. 2022 International Conference on Decision Aid Sciences and Applications, DASA 2022, 326–329. doi:10.1109/DASA54658.2022.9765005.

[36] Jahanbakhshi, A., Momeny, M., Mahmoudi, M., & Zhang, Y. D. (2020). Classification of sour lemons based on apparent defects using stochastic pooling mechanism in deep convolutional neural networks. Scientia Horticulturae, 263, 1–10. doi:10.1016/j.scienta.2019.109133.

[37] Wang, Y., Yang, L., Chen, H., Hussain, A., Ma, C., & Al-gabri, M. (2022). Mushroom-YOLO: A deep learning algorithm for mushroom growth recognition based on improved YOLOv5 in agriculture 4.0. 2022 IEEE 20th International Conference on Industrial Informatics (INDIN), Perth, Australia. doi:10.1109/indin51773.2022.9976155.

[38] Sevilla, W. H., Hernandez, R. M., Ligayo, M. A. D., Costa, M. T., & Quismundo, A. Q. (2022). Machine Vision Recognition System of Edible and Poisonous Mushrooms Using a Small Training Set-Based Deep Transfer Learning. 2022 International Conference on Decision Aid Sciences and Applications (DASA), Chiangrai, Thailand. doi:10.1109/dasa54658.2022.9765046.

[39] Behera, S. K., Rath, A. K., & Sethy, P. K. (2021). Maturity status classification of papaya fruits based on machine learning and transfer learning approach. Information Processing in Agriculture, 8(2), 244–250. doi:10.1016/j.inpa.2020.05.003.

[40] Islam, Md. A., Islam, Md. S., Hossen, Md. S., Emon, M. U., Keya, M. S., & Habib, A. (2020). Machine Learning based Image Classification of Papaya Disease Recognition. 2020 4th International Conference on Electronics, Communication and Aerospace Technology (ICECA), Coimbatore, India. doi:10.1109/iceca49313.2020.9297570.

[41] Patil, A., & Lad, K. (2022). Feature Selection for Chili Leaf Disease Identification Using GLCM Algorithm. Smart Innovation, Systems and Technologies, 251, 359–365. doi:10.1007/978-981-16-3945-6_35.

[42] Aminuddin, N. F., Joret, A., Zulkifli, S. A., Abdul Kadir, H., Morsin, M., & Tukiran, Z. (2023). Computational Approaches Based on Image Processingfor Automated Disease Identification on Chili Leaf Images: A Review. Emerging Advances in Integrated Technology, 3(2), 11–26. doi:10.30880/emait.2022.03.02.002.

[43] Tan, J., Sutanto, B. C., Marvelim, D., Pratama, G. D., & Hasana, S. (2023). Chili Plant Health Status Classification Using Random Forest. 2023 4th International Conference on Artificial Intelligence and Data Sciences (AiDAS), IPOH, Malaysia. doi:10.1109/aidas60501.2023.10284701.

[44] Anbananthen, K. S. M., Subbiah, S., Baskar, S. G., Selvaraj, R., Krishnan, J., Kannan, S., & Chelliah, D. (2023). The Eye: A Light Weight Mobile Application for Visually Challenged People Using Improved YOLOv5l Algorithm. Emerging Science Journal, 7(5), 1636-1652. doi:10.28991/ESJ-2023-07-05-011.

[45] Cruz-Domínguez, O., Carrera-Escobedo, J. L., Guzmán-Valdivia, C. H., Ortiz-Rivera, A., García-Ruiz, M., Durán-Muñoz, H. A., Vidales-Basurto, C. A., & Castaño, V. M. (2021). A novel method for dried chili pepper classification using artificial intelligence. Journal of Agriculture and Food Research, 3. doi:10.1016/j.jafr.2021.100099.

[46] Aldabbagh, A. D. A., Hairu, C., & Hanafi, M. (2020). Classification of Chili Plant Growth using Deep Learning. 2020 IEEE 10th International Conference on System Engineering and Technology (ICSET), Shah Alam, Malaysia. doi:10.1109/icset51301.2020.9265351.

[47] Saad, W. H. M., Karim, S. A. A., Razak, M. S. J. A., Radzi, S. A., & Yussof, Z. M. (2020). Classification and detection of chili and its flower using deep learning approach. Journal of Physics: Conference Series, 1502. doi:10.1088/1742-6596/1502/1/012055.

[48] Purwaningsih, T., Anjani, I. A., & Utami, P. B. (2018). Convolutional Neural Networks Implementation for Chili Classification. International Symposium on Advanced Intelligent Informatics (SAIN), Yogyakarta, Indonesia. doi:10.1109/sain.2018.8673373.

[49] Ram, P. P. V. S., Yaswanth, K. V. S., Kamepalli, S., Sankar, B. S., & Madupalli, M. (2023). Deep Learning Model YOLOv5 for Red Chilies Detection from Chilly Crop Images. 2023 IEEE 8th International Conference for Convergence in Technology (I2CT), Lonavla, India. doi:10.1109/i2ct57861.2023.10126327.

[50] Yin, L. L., Zainudin, M. N. S., Saad, W. H. M., Sulaiman, N. A., Idris, M. I., Kamarudin, M. R., Mohamed, R., & Razak, M. S. J. A. (2023). Analysis Recognition of Ghost Pepper and Cili-Padi using Mask-RCNN and YOLO. Przeglad Elektrotechniczny, 2023(8), 92–97. doi:10.15199/48.2023.08.15.

[51] Mayalekshmi, K. M., Ranjan, A., & Machavaram, R. (2023). In-field Chilli Crop Disease Detection Using YOLOv5 Deep Learning Technique. 2023 IEEE 8th International Conference for Convergence in Technology (I2CT), Lonavla, India. doi:10.1109/I2CT57861.2023.10126468.

[52] Hing, Y. S., Wan, W. Y., & Nugroho, H. (2021). Objective Tool for Chili Grading Using Convolutional Neural Network and Color Analysis. In Advances in Robotics, Automation and Data Analytics: Selected Papers from iCITES 2020, 315-324. doi:10.1007/978-3-030-70917-4_30.

[53] Ibrahim, M. F., Zainudin, M. S., Idris, M. I., Saad, W. M., Kamarudin, M. R., Sulaiman, N. A., & Mohamed, R. (2023). Detection and Classifying of Chili Fruits Variations using YOLOv5. KZYJC, 38(4), 1363-1376.

[54] Zainudin, M. S., Azlan, M. S., Yin, L. L., Saad, W. M., Idris, M. I., Muhammad, S., & Razak, M. S. J. A. (2022). Analysis on localization and prediction of depth chili fruits images using YOLOv5. International Journal of Advanced Technology and Engineering Exploration, 9(97), 1786. doi:10.19101/IJATEE.2021.876501.

[55] Tan, Z., Chen, B., Sun, L., Xu, H., Zhang, K., & Chen, F. (2023). Pepper Target Recognition and Detection Based on Improved YOLO v4. Information Technology and Control, 52(4), 878–886. doi:10.5755/j01.itc.52.4.34183.

[56] Hespeler, S. C., Nemati, H., & Dehghan-Niri, E. (2021). Non-destructive thermal imaging for object detection via advanced deep learning for robotic inspection and harvesting of chili peppers. Artificial Intelligence in Agriculture, 5, 102–117. doi:10.1016/j.aiia.2021.05.003.

[57] Manan, A. A. A., Razman, M. A. M., Khairuddin, I. M., & Shapiee, M. N. A. (2020). Chili Plant Classification using Transfer Learning models through Object Detection. Mekatronika, 2(2), 23-27. doi:10.1007/978-981-19-2095-0_46.

[58] Sudianto, Herdiyeni, Y., Haristu, A., & Hardhienata, M. (2020). Chilli Quality Classification using Deep Learning. 2020 International Conference on Computer Science and Its Application in Agriculture (ICOSICA), Bogor, Indonesia. doi:10.1109/icosica49951.2020.9243176.

[59] Xu, R., Lin, H., Lu, K., Cao, L., & Liu, Y. (2021). A forest fire detection system based on ensemble learning. Forests, 12(2), 217. doi:10.3390/f12020217.

[60] Wang, C.-Y., Mark Liao, H.-Y., Wu, Y.-H., Chen, P.-Y., Hsieh, J.-W., & Yeh, I.-H. (2020). CSPNet: A New Backbone that can Enhance Learning Capability of CNN. 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), Seattle, United States. doi:10.1109/cvprw50498.2020.00203.

[61] Wang, K., Liew, J. H., Zou, Y., Zhou, D., & Feng, J. (2019). PANet: Few-Shot Image Semantic Segmentation with Prototype Alignment. 2019 IEEE/CVF International Conference on Computer Vision (ICCV), Seoul, Korea (South). doi:10.1109/iccv.2019.00929.

[62] Ren, S., He, K., Girshick, R., & Sun, J. (2017). Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks. IEEE Transactions on Pattern Analysis and Machine Intelligence, 39(6), 1137–1149. doi:10.1109/TPAMI.2016.2577031.

[63] Aishwarya, N., Manoj Prabhakaran, K., Debebe, F. T., Reddy, M. S. S. A., & Pranavee, P. (2023). Skin Cancer diagnosis with Yolo Deep Neural Network. Procedia Computer Science, 220, 651–658. doi:10.1016/j.procs.2023.03.083.